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Bayesian Network Based Multiagent System— Application in E-Marketplace

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Abstract—The concept of e-marketplace has been touted through the extensive use of the Internet. However, the task of filtering the potential supplier base in the e-marketplace is tedious while evaluating all the necessary qualitative and quantitative decision factors. Since the buyers have to evaluate and select suppliers by conveying necessary contingent information among potential suppliers, a superior structure of a multiagent system is constructed in this study to present the characteristics of the e-marketplace. The illustrative examples' results prevail to show that, after communicating among the virtual e-marketplace, the suppliers did know how to adapt their strategies to accommodate buyers' demand. On the other hand, the buyers also know which supplier is the most appropriate for short term as well as long term.

Keywords—E-marketplace, Supplier selection, Bayesian belief networks, Multiagent system.

1. INTRODUCTION

For the fast evolving e-commerce, most of the large companies are looking for suppliers which can help them to achieve a competitive position and sustain it over long periods. The above-mentioned advantage can be obtained while considering all contingent factors, such as good merchandise quality, better customer service, and efficient communication among suppliers base. In such a manner, most buyers of raw material and industrial parts search for potential suppliers through the Internet, where they can utilize sufficient information to evaluate, compare, and then select appropriate suppliers efficiently. Although long-term alliances have become very popular, small-to-median size companies still focus on short-term buyer-supplier relationship only, where the e-marketplace can substantially fulfill such a requirement. However, McCutcheon and Stuart [1] commented if only focusing on the short-term factors, such as cost, quality, and delivery only, the corresponding companies would consequently suffer long-term negative impact resulting from such myopic consideration.

Furthermore, it is very common for suppliers to obtain buyers' detail purchasing behaviors through referees in order to adapt their marketing strategies in an e-marketplace. On the other

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hand, buyers' procurement related activities, such as searching products, finding appropriate suppliers, and bidding with them, also require sufficient reference of suppliers in the corresponding field. These kinds of information are usually expensive and not neutral. Accordingly, this study attempts to resolve such drawbacks via intelligent multiagent architecture in the e-marketplace to enhance the efficiency as well as quality.

Moreover, this study intends to provide a better insight for short-term supplier selection employing the benefit of long-term alliance, where agent technology is utilized to represent subdomain knowledge experts and to coordinate all the required quantitative and qualitative factors in considering the fitness of potential suppliers in the e-marketplace.

2. LITERATURE REVIEW

With the trend to outsource more and more of value-added content, strategic sourcing is growing in its importance for most firms [2]. For such a reason, many companies are seeking an efficient approach to manage their supply base through alliance in order to eliminate uncertainty from the external supply chain [3]. A lot of literature has surveyed the issues in selection of supplier alliance partners [1,4,5]. Among them, there are two major categories of impact factor to choose supplier alliance partners: one relates to the technology being used to select a supplier [6]; the other relates to the ability to develop mutual goodwill trust with the target supplier [7,8]. Empirical research by Toni and Nassimbeni [9] on Italian plants verified that advanced buyer-supplier interaction and cooperative supply management exhibit a predictive validity of the plant performances. Accordingly, companies should consider long-term supplier alliance during the short-term planning horizon as well.

Agent technology has been applied in many domains [10,11], in which the common systematic approach is depicted by Figure 1 [12,13]. Each agent, which inherits its own constraints and set of actions, will react to the environmental stimulation with its appropriate action policy. Such reactive ability can be employed to handle tedious decisions for human beings and offer effective information while making decisions. Furthermore, in order to utilize each agent to represent the subdomain of the whole environment of interest, a multiagent system will be constructed. This kind of system requires corresponding agents to retain their inherent autonomy and to cooperate with others. In practice, the multiagent system has proved to solve many problems and accomplish complex tasks for human beings [10,11,14].

In any e-marketplace, suppliers and buyers do not know each other's detail policy, such as willingness to improve customer's service level, etc. However, they can evaluate and infer the

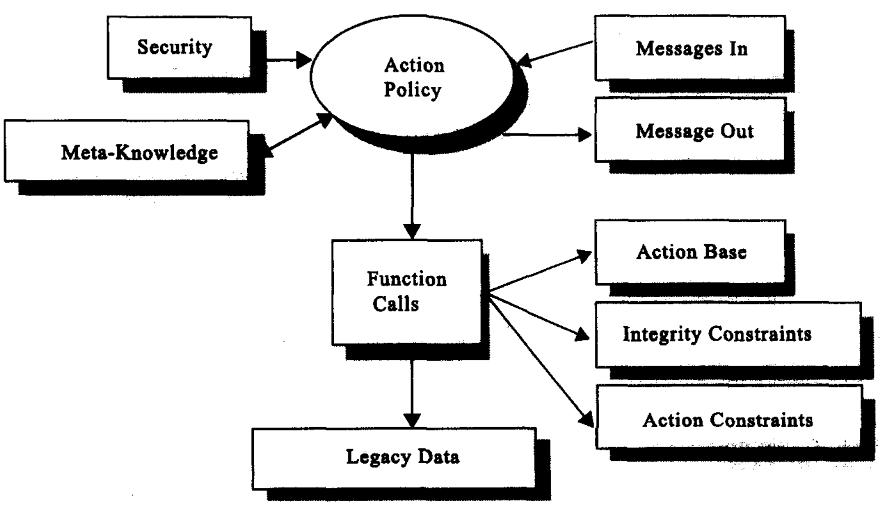

Figure 1. Common structure of the agent system.

opposite side's current conditions via their historic reputation and then decide how to react and adapt their policies towards the target partners. Bayesian belief networks (BBNs), advanced by Pearl, have become an important paradigm for representing and reasoning with uncertainty, and have been constructed in a number of different application areas [15]. This kind of model includes methods for constructing learning networks, storing probabilistic information, and evidence propagation scheme. BBNs utilize graphical representations of uncertain knowledge, which can be easily interpreted. First of all, the structure of the graph forms qualitative relationships between domain variables. Second, quantitative aspects of knowledge are represented by a set of conditional probability tables. Finally, the nodes of BBNs reflect these qualitative and quantitative relationships in the influence graph.

Accordingly, a BBN is utilized to model the structure of the entire system to select suppliers and to construct inference ability of the agent about their relationship and communication in this study. To model short-term supplier selection in an e-marketplace through a multiagent system, the corresponding agents have to exhibit their inference ability, where BBNs can support such a characteristic [16–18]. In addition, BBNs work as a mathematical model to represent uncertain information, which can be utilized to model the relationship among agents as a probabilistic-based expert system [19]. In the following section, BBNs are employed to help infer the contribution caused by the events from certain agents, which is further used to select suppliers in an e-marketplace.

3. METHODOLOGY

In this section, the method to construct a desired multiagent supplier selection system is proposed. In order to apply a probabilistic approach to establish the corresponding multiagent society, an efficient framework of communication between supplier and buyer agents is also presented.

3.1. Determining Short-Term Suppliers' Selection Decision Factors for a Single Agent

In order not to suffer from long-term negative impact, the consideration of the short-term supplier selection in an e-marketplace should cover similar factors to pursue an alliance-like relationship. McCutcheon and Stuart [1] composed three categories of decision factors, which are normative advice about suppliers to seek for alliance, drivers for targeting suppliers, and variables affecting alliance development. Those factors consist of both qualitative and quantitative considerations for suppliers and buyers. Accordingly, the proposed model utilizes the above factors to construct agents for both suppliers and buyers, which are shown in Tables 1 and 2.

Intuitively, some of the above factors are conditionally interdependent. For example, if the probabilities of better reputation and two-way information sharing are high, the probability of taking better trust towards suppliers will be high as well. Their interdependence and conditional

Table 1. Qualitative and quantitative factors of supplier side's agent.

Supplier Agent	
Cost reliability (CR)	Gain marketing advantage (GMA)
Reputation (Re)	Trust (Tr)
Quality reliability (QR)	Mutual goals (MG)
Not capable of becoming a competitor (NC)	Two-way information sharing (TWIS)
Provide high value-added product (PVAP)	Symmetry (Sy)
Willing to adapt to the buyers' policy (WTAB)	Compatibility (Comp)
Help to improve customers' service level (HISL)	

Table 2. Qualitative and quantitative factors of buyer side's agent.

Buyer Agent	
Cost and quality consideration (CQ)	Secure stable or growth market (SGM)
High value-added (Hva)	Reputation of supplier (ReoS)
Competitor in the future (Cf)	Trustworthiness of supplier (TroS)
Critical technology in the future (CT)	Mutual goals (MG)
Different and complementary (DiCm)	Two-way information sharing (TWIS)
Ability to influence through power and interdependence (ATI)	Symmetry (Sy)
Improve customers' service level (ICSL)	Compatibility (Comp)
Gain marketing advantage (GMA)	

probabilities can be analytically obtained from experts and mathematical models as mentioned in Section 3.2.

3.2. Configure the Single Agent

From Tables 1 and 2, many subdomain decision factors can be identified, such as reputation of suppliers, trustworthiness of suppliers, and cost-concerned on suppliers. These qualitative and quantitative factors are somewhat interdependent and can be modeled as variables for corresponding subdomain agent. To construct a subdomain single agent, an autonomous learning method, which includes both observed data and construction procedure, is used to transfer expert knowledge to a BBN for initialization. Furthermore, such an initial structure is used to conduct the learning method, which is modified from the approach of Gemela [16]. The proposed procedure is given as follows.

STEP 1. INITIALIZATION. Utilize the knowledge of experts or decision makers to initialize the BBN, which is to establish necessary connections among impact factors given in Tables 1 and 2. Furthermore, directions of the arrows between any connected variables must be decided, accordingly.

STEP 2. FITNESS EVALUATION. The arrows or connections among variables can be added or eliminated by utilizing equation (1) to measure the correspondent fitness of the current model structure:

$$\mu(M) = w_1 \frac{\operatorname{Div}\left(\hat{P}, P_M\right)}{\operatorname{Div}\left(\hat{P}, P_{S_{\min}}\right)} + w_2 \frac{c(M) - c\left(S_{\min}\right)}{c\left(S_{\max}\right)} + w_3 \frac{U - u(M)}{U}, \tag{1}$$

$$\operatorname{Div}\left(\hat{P}, P_M\right) = \sum_x \hat{P}(x) \log \frac{\hat{P}(x)}{P_M(x)}, \tag{2}$$

where

$S_{\min}, S_{\max}$ the model without arrow and complete graph, respectively;
$c(\cdot)$ the complexity of a model, which is measured by the method of minimum description length (MDL) [15,20];
$u(\cdot)$ the number of expert's arrows presented in the model;
U the total number of arrows given by experts;
$\hat{P}$ the empirical probability distribution;
P_M the probability distribution represented by the model;
x the node variables;
w_i the weights of measures according to decision maker's preferences.

Equations (1) and (2) represent three requirements of the proposed BBN's structure, which are accuracy, complexity, and meeting expert's requirement. These three requirements must be considered concurrently in order to find the best structure of the desired agent system. In this stage, the structure with smaller fitness value will be eliminated in order to maintain the better alternatives for the future pairwise comparisons.

STEP 3. ITERATION. This stage is to choose the best structure of desired BBN by fitting the model with the observed data and experts' knowledge. Through iterations, the most appropriate BBN configuration to select supplier can be obtained with the largest fitness value of $\mu(M)$.

3.3. Expand System Configuration from Single Agent to Multiagent System

The BBNs as an inference network consist of several decision variable nodes connected with directed line, which can be obtained by the procedure given in Section 3.2. For example, the BBN structure for a buyer agent can be illustrated in Figure 2 after iterations. Such BBN consists of joint probability distribution of the parent nodes and their corresponding child nodes. For example, the reputation of the respective supplier (ReoS) and its desire to be influenced by its customer (ATI) can both contribute to the reliability that a buyer would conceive its supplier.

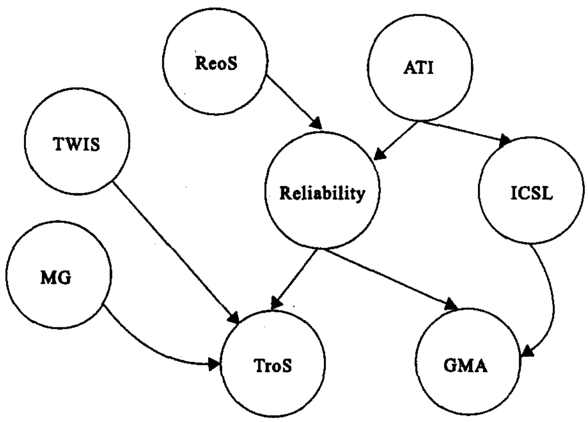

Figure 2. Single Bayesian network based agent for selecting supplier.

In this study, such a kind of agent can be represented as a directed acyclic graph (DAG), $D_i = (N^i, E^i)$, in which N and E denote the nodes and arcs, respectively, where the subscript is used to denote the index of the respective agent. In order to perform selection more efficiently in an e-marketplace, the authors reform the configuration by combining them into a multiagent system, where the procedures are given as follows.

STEP 1. COMBINE ALL AGENTS OF E-MARKETPLACE INTO A HYPERTREE STRUCTURE. Since multiagent system D is the union of all the DAGs, the first step is to combine all the supplier and buyer agents into a hypertree structure, where each hypernode represents a supplier/buyer agent. Furthermore, each hypernode, consisting of decision variables, is a subnet of the BBN structure for the multiagent system. The hypertree of such multiagent system can be constructed as an example in Figure 3.

STEP 2. CONVERT SINGLE AGENT TO A JUNCTION TREE (JT) (CLIQUE TREE). In order to perform communication among supplier and buyer agents, the configuration of each single agent has to be converted as a junction tree through moralization [21] and triangulation [22–25], which is depicted in Figure 4 as an example.

STEP 3. DETERMINE LINKAGES AMONG EACH SET OF JUNCTION TREES ACCORDING TO d-SEPSET INTERSECTION. The communicating connections among each agent, namely a junction tree, are represented as hyperlinks, which are defined as d-sepsets [26]. That is,

$$\forall \text{DAGs}, \qquad D^i = \left(N^i, E^i\right) \text{ in a single agent,}$$

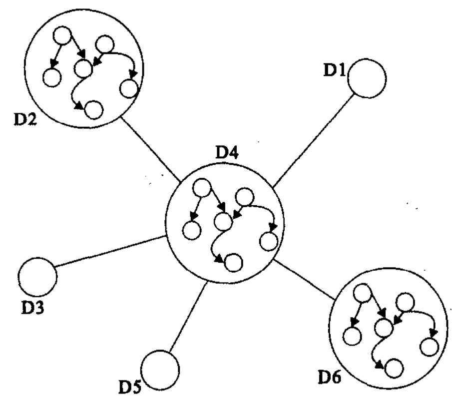

Figure 3. The illustrating hypertree structure of a multiagent system.

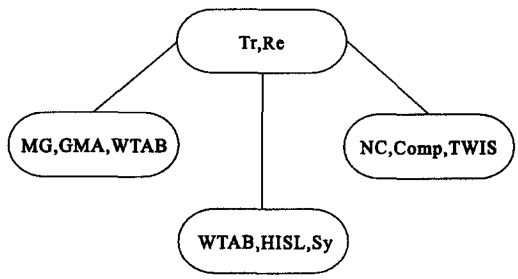

Figure 4. Junction tree example for supplier agent.

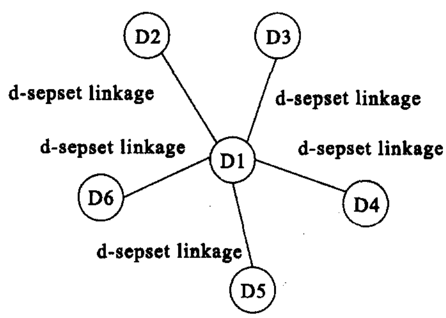

Figure 5. Linked junction forest for multiagent supplier selection system.

where Union, $D = (\bigcup_i N, \bigcup_i E)$. Then,

$$\forall \text{any two DAGs in } D, \qquad \text{the intersection linkage } I = \left(N^1 \cap N^2\right) \text{ is a } d\text{-sepset}$$

if $\forall A_i \in I$, its parents π_i in D is either $\pi_i \subseteq N^1$ or $\pi_i \subseteq N^2$.

This d-sepset will render any pair of subnets conditionally independent. Thereafter, the basic dependency assumption embedded in BBNs will constrain each node to be conditionally independent from its nonparent nodes. Accordingly, the joint probability distribution (JPD), P, for each node in this proposed BBN can be obtained from $P = \Pi_i p(A_i \mid \pi_i)$.

STEP 4. FORM A LINKED JUNCTION FOREST (LJF) BASED ON THE d-SEPSET LINKAGES. Since all the agents are grouped as a society in an e-marketplace, the integrated multiagent system is a triplet (N, E, P), where the nodes, i.e., single agents, are connected with corresponding d-sepset linkages. Based on the above, the multiagent e-marketplace can be constructed as a linked junction forest in Figure 5. While the d-sepset linkages were established among agents, the communication will go through these linkages, which can improve the communication efficiency in a multiagent system [26].

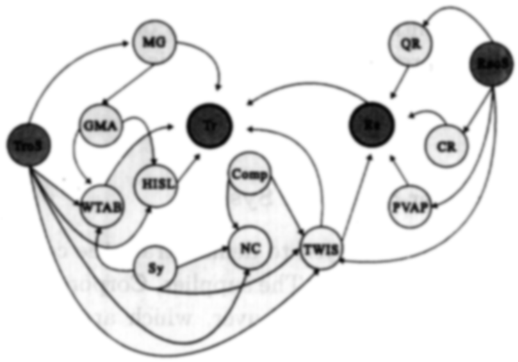

Figure 6. Single agent of supplier side.

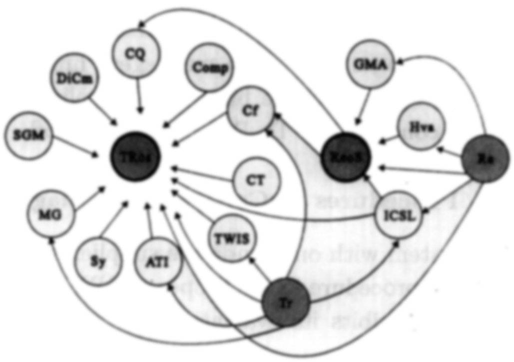

Figure 7. Single agent of buyer side.

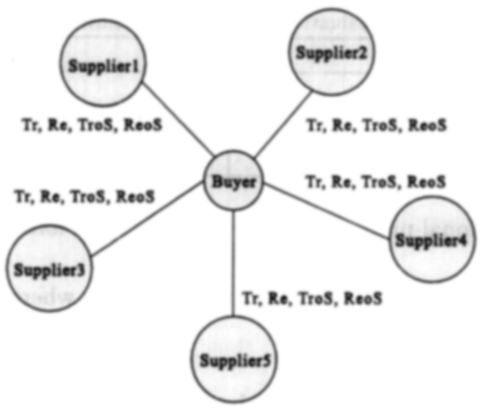

Figure 8. Multiagent society in e-marketplace.

4. ILLUSTRATIVE EXAMPLE

In this section, the proposed supplier-selection multiagent system is demonstrated by an example in which the buyer communicates with potential suppliers to make a decision out of the potential candidates. The details of the example are given as follows.

(1) After applying the proposed procedures to construct the supplier-selection multiagent system, configurations of the supplier's agents and buyer's agents are illustrated in Figures 6 and 7, respectively.

(2) Each quantitative or qualitative factor has two levels of 1 and 2, in which 1 represents its inferior condition for the corresponding with 2 representing the superior condition.. As to the buyer side, while the value of Cf is 1 means the buyer evaluates the corresponding supplier without any attempt to be a competitor in the future. However, if the value Cf is 2, such a supplier has been valued with a strong attempt to compete with the buyer in the near future.

(3) For each linkage between factors, field experts have to contribute the corresponding conditional probability. The probability tables are shown in the Appendix. For example, by making sacrifices and showing their care about their partners, the suppliers have to develop better reputations. Furthermore, if the buyers perceive the suppliers with higher reputations, they will be more likely to trust them. Accordingly, a positive reputation is likely to increase the trust.

(4) Under the basic dependency assumption from the BBNs, the factor node is conditionally independent to nonparent factors. Then, the joint probability for each node is given as $P(A_i) = \Pi_i p(A_i \mid \pi_i)$, where A_i is the evaluation of a decision factor and π_is are A_i's parent nodes.

(5) After applying the procedure to establish a multiagent system based on the d-sepset linkages, the entire multiagent linked junction forest to select supplier is represented in Figure 8, where buyer and supplier agents communicate with each other by the linkage consisting of Tr, Re, TroS, and ReoS.

4.1. Procedures to Construct Multiagent Supplier-Selection System

A system with one candidate supplier and one buyer is employed to demonstrate the communication procedure in the proposed BBN-based multiagent system. The supplier, Corporation A, initially exhibits its evaluations according to the environment and buyer, which are given in Table 3.

Table 3. Initial value of factors inherited from the candidate supplier.

Corporation A's Initial Evaluation of Factors from Environment and Buyer Side	
Sy = 1	CT = 1
Comp = 1	PVAP = 1
QR = 1	MG = 1
CR = 1	DiCm = 1

Accordingly, the conditional probabilities are formulated as follows:

$$P(A = a_i) = \prod P(A = a_i \mid \text{Parent}(A)), \qquad \text{where } a_i = 1 \text{ or } 2.$$

Then $A = a$, if $P(a) = \max(P(A = a_i))$.

From the BBN approach, the following can be obtained as an example:

$$\begin{aligned} P(\text{Re} = 1) &= P(\text{Re} = 1 \mid \text{QR} = 1)P(\text{Re} = 1 \mid \text{CR} = 1)P(\text{Re} = 1 \mid \text{PVAP} = 1) \\ &\quad \times P(\text{Re} = 1 \mid \text{TWIS} = 2) \\ &= 0.89 \times 0.79 \times 0.83 \times 0.19 = 0.1108, \\ P(\text{Re} = 2) &= P(\text{Re} = 2 \mid \text{QR} = 1)P(\text{Re} = 2 \mid \text{CR} = 1)P(\text{Re} = 2 \mid \text{PVAP} = 1) \\ &\quad \times P(\text{Re} = 2 \mid \text{TWIS} = 2) \\ &= 0.11 \times 0.21 \times 0.17 \times 0.81 = 0.0031. \end{aligned}$$

Then, the evaluation of Re is determined to be 1 due to $P(\text{Re} = 1)$ possessing larger probability.

After evaluating all the factors, Corporation A issues its status evaluation, which is given in Table 4.

The supplier agent utilizes the above to communicate with the buyer agent. In return, the buyer agent modifies its belief after obtaining Corporation A's information about Tr and Re. The updates from the buyer agent towards Corporation A are given in Table 5.

Accordingly, the following phenomenon from the first stage communication can be reached as follows.

(1) Since the buyer agent has not fed back its update belief, namely the evaluation of TroS and ReoS, it did not have any influence on the supplier agent's strategies.
(2) Under the strategy of QR = 1, CR = 1, PVAP = 1, and TWIS = 2, the supplier releases its reputation (Re) of 1 with conditional probability of 0.1108, which means it possesses a higher probability to have a poor reputation.
(3) Under the strategy of Re = 1, TWIS = 2, MG = 1, HISL = 1, WTAB = 1, and MG = 1, the supplier releases its trust (Tr) of 1 with conditional probability of 0.0607, which means it possesses a higher probability to have poor trust.

Table 4. Status evaluation of supplier agent (Corporation A).

<table>
<tr><td>QR = 1</td><td colspan="2">CR = 1</td><td colspan="2">PVAP = 1</td><td>TWIS = 2</td></tr>
<tr><td colspan="6">$P(\mathrm{Re} = 1 \mid \mathrm{QR} = 1, \mathrm{CR} = 1, \mathrm{PVAP} = 1, \mathrm{TWIS} = 2) = 0.1108$</td></tr>
<tr><td colspan="6">$P(\mathrm{Re} = 2 \mid \mathrm{QR} = 1, \mathrm{CR} = 1, \mathrm{PVAP} = 1, \mathrm{TWIS} = 2) = 0.0031$</td></tr>
<tr><td>Re = 1</td><td>TWIS = 2</td><td>NC = 1</td><td>HISL = 1</td><td>WTAB = 1</td><td>MG = 1</td></tr>
<tr><td colspan="6">$P(\mathrm{Tr} = 1 \mid \mathrm{Re} = 1, \mathrm{TWIS} = 2, \mathrm{NC} = 1, \mathrm{HISL} = 1, \mathrm{WTAB} = 1, \mathrm{MG} = 1) = 0.0607$</td></tr>
<tr><td colspan="6">$P(\mathrm{Tr} = 2 \mid \mathrm{Re} = 1, \mathrm{TWIS} = 2, \mathrm{NC} = 1, \mathrm{HISL} = 1, \mathrm{WTAB} = 1, \mathrm{MG} = 1) = 0.000036$</td></tr>
</table>

Table 5. Supplier's evaluation of buyer agent.

<table>
<tr><td colspan="3">ICSL = 1</td><td colspan="2">Re = 1</td><td colspan="3">Hva = 1</td><td colspan="3">GMA = 1</td></tr>
<tr><td colspan="11">$P(\mathrm{ReoS} = 1 \mid \mathrm{ICSL} = 1, \mathrm{Re} = 1, \mathrm{Hva} = 1, \mathrm{GMA} = 1) = 0.6296$</td></tr>
<tr><td colspan="11">$P(\mathrm{ReoS} = 2 \mid \mathrm{ICSL} = 1, \mathrm{Re} = 1, \mathrm{Hva} = 1, \mathrm{GMA} = 1) = 1.071 \times 10^{-5}$</td></tr>
<tr><td>CT = 1</td><td>Tr= 1</td><td>TWIS = 1</td><td>ATI = 1</td><td>Sy = 1</td><td>MG = 1</td><td>SGM = 2</td><td>DiCm = 1</td><td>CQ = 1</td><td>Comp = 1</td><td>Cf = 2</td></tr>
<tr><td colspan="11">$P\left(\mathrm{TroS} = 1 \,\middle|\, \begin{matrix} \mathrm{CT} = 1,\ \mathrm{Tr} = 1,\ \mathrm{TWIS} = 1,\ \mathrm{ATI} = 1,\ \mathrm{Sy} = 1,\ \mathrm{MG} = 1, \\ \mathrm{SGM} = 2,\ \mathrm{DiCm} = 1,\ \mathrm{CQ} = 1,\ \mathrm{Comp} = 1,\ \mathrm{Cf} = 2 \end{matrix}\right) = 0.03187$</td></tr>
<tr><td colspan="11">$P\left(\mathrm{TroS} = 2 \,\middle|\, \begin{matrix} \mathrm{CT} = 1,\ \mathrm{Tr} = 1,\ \mathrm{TWIS} = 1,\ \mathrm{ATI} = 1,\ \mathrm{Sy} = 1,\ \mathrm{MG} = 1, \\ \mathrm{SGM} = 2,\ \mathrm{DiCm} = 1,\ \mathrm{CQ} = 1,\ \mathrm{Comp} = 1,\ \mathrm{Cf} = 2 \end{matrix}\right) = 2.39 \times 10^{-9}$</td></tr>
</table>

4.2. Update Belief Procedure After Communication

Whenever the buyer agent finished its evaluation over the supplier agent's policies during the communication period, two critical values, TroS and ReoS, will be fed back to the supplier agent. Thereafter, such feedback will impose influence on the conditional probability of decision factors for the supplier agent. Table 6 concludes the updated results of the supplier agent after factoring in the evaluation from the buyer agent.

After updating the policy, the supplier agent releases a new policy and tries to improve the buyer agent's critique by triggering the buyer agent to update the belief again. The result is shown in Table 7.

Table 6. Updated policy of the supplier agent after communication.

<table>
<tr><td>QR = 2</td><td colspan="2">CR = 2</td><td colspan="2">PVAP = 2</td><td>TWIS = 2</td></tr>
<tr><td colspan="6">$P(\mathrm{Re} = 1 \mid \mathrm{QR} = 2, \mathrm{CR} = 2, \mathrm{PVAP} = 2, \mathrm{TWIS} = 2) = 0.00421$</td></tr>
<tr><td colspan="6">$P(\mathrm{Re} = 2 \mid \mathrm{QR} = 2, \mathrm{CR} = 2, \mathrm{PVAP} = 2, \mathrm{TWIS} = 2) = 0.1332$</td></tr>
<tr><td>Re = 2</td><td>TWIS = 2</td><td>NC = 2</td><td>HISL = 1</td><td>WTAB = 1</td><td>MG = 1</td></tr>
<tr><td colspan="6">$P(\mathrm{Tr} = 1 \mid \mathrm{Re} = 2, \mathrm{TWIS} = 2, \mathrm{NC} = 2, \mathrm{HISL} = 1, \mathrm{WTAB} = 1, \mathrm{MG} = 1) = 0.009884$</td></tr>
<tr><td colspan="6">$P(\mathrm{Tr} = 2 \mid \mathrm{Re} = 2, \mathrm{TWIS} = 2, \mathrm{NC} = 2, \mathrm{HISL} = 1, \mathrm{WTAB} = 1, \mathrm{MG} = 1) = 0.001641$</td></tr>
</table>

Table 7. Updated critique of the buyer agent after communication.

<table>
<tr><td colspan="2">ICSL = 1</td><td colspan="3">Re = 2</td><td colspan="3">Hva = 2</td><td colspan="3">GMA = 2</td></tr>
<tr><td colspan="11">$P(\mathrm{ReoS} = 1 \mid \mathrm{ICSL} = 1, \mathrm{Re} = 2, \mathrm{Hva} = 2, \mathrm{GMA} = 2) = 0.0122$</td></tr>
<tr><td colspan="11">$P(\mathrm{ReoS} = 2 \mid \mathrm{ICSL} = 1, \mathrm{Re} = 2, \mathrm{Hva} = 2, \mathrm{GMA} = 2) = 0.003926$</td></tr>
<tr><td>CT = 1</td><td>Tr = 1</td><td>TWIS = 2</td><td>ATI = 1</td><td>Sy = 1</td><td>MG = 1</td><td>SGM = 2</td><td>DiCm = 1</td><td>CQ = 1</td><td>Comp = 1</td><td>Cf = 2</td></tr>
<tr><td colspan="11">$P\left(\mathrm{TroS} = 1 \,\middle|\, \begin{matrix} \mathrm{CT} = 1,\ \mathrm{Tr} = 1,\ \mathrm{TWIS} = 2,\ \mathrm{ATI} = 1,\ \mathrm{Sy} = 1,\ \mathrm{MG} = 1, \\ \mathrm{SGM} = 2,\ \mathrm{DiCm} = 1,\ \mathrm{CQ} = 1,\ \mathrm{Comp} = 1,\ \mathrm{Cf} = 2 \end{matrix}\right) = 0.003853$</td></tr>
<tr><td colspan="11">$P\left(\mathrm{TroS} = 2 \,\middle|\, \begin{matrix} \mathrm{CT} = 1,\ \mathrm{Tr} = 1,\ \mathrm{TWIS} = 2,\ \mathrm{ATI} = 1,\ \mathrm{Sy} = 1,\ \mathrm{MG} = 1, \\ \mathrm{SGM} = 2,\ \mathrm{DiCm} = 1,\ \mathrm{CQ} = 1,\ \mathrm{Comp} = 1,\ \mathrm{Cf} = 2 \end{matrix}\right) = 2.364 \times 10^{-8}$</td></tr>
</table>

To compare Table 5 with Table 7, which are the critiques of the buyer agent before and after communication, respectively, the following insights can be found.

(1) After modifying the strategy of QR = 2, CR = 2, PVAP = 2, and TWIS = 2 by given the critique of ReoS and TroS, the supplier agent seems to possess higher probability with a better reputation than before. It means the supplier agent attempts to earn a higher reputation while it recognizes the reputation evaluated by its target buyer is poor.

(2) After updating the belief, the supplier agent decreases the conditional probability of having poor trustworthiness and increases that of having an excellent one. It means the supplier tries to improve the entire critique via modifying its strategies.

(3) After the supplier agent releases its modification, the buyer agent then updates its critique towards the supplier agent with less probability of being poorly trustworthy and having a bad reputation, and increase temptation of good trust and reputation. By comparing Tables 5 and 7, the probability of believing the supplier trustworthy (i.e., TroS = 2) after communication is much higher than without mutual communication. That is to say, the supplier agent can improve its probability of being selected via modification of its policy.

4.3. Scenario Analysis

In order to demonstrate the robustness of the proposed model, an extreme case is used here to illustrate the ability of selecting the right supplier. Herein, Corporation B is assumed to have as strong an intention as Corporation A to adapt the buyer's policy. In such a manner, Corporation B has the same conditional probability tables as Corporation A except that it possesses absolutely superior conditions, which are given in Table 8.

Following the iteration procedure in Section 4.1, the results are depicted in Tables 9 and 10.

Table 8. Initial value of factors inherited from the excellent supplier.

<table>
<tr><td colspan="2">Corporation B's Initial Evaluating Values of Factors under Environment or Buyer Side</td></tr>
<tr><td>Sy = 2</td><td>CT = 2</td></tr>
<tr><td>Comp = 2</td><td>PVAP = 2</td></tr>
<tr><td>QR = 2</td><td>MG = 2</td></tr>
<tr><td>CR = 2</td><td>DiCm = 2</td></tr>
</table>

Table 9. Evaluation of supplier agent.

<table>
<tr><td>QR = 2</td><td colspan="2">CR = 2</td><td colspan="2">PVAP = 2</td><td>TWIS = 2</td></tr>
<tr><td colspan="6">$P(\text{Re} = 1 \mid \text{QR} = 2,\ \text{CR} = 2,\ \text{PVAP} = 2,\ \text{TWIS} = 2) = 0.00421$</td></tr>
<tr><td colspan="6">$P(\text{Re} = 2 \mid \text{QR} = 2,\ \text{CR} = 2,\ \text{PVAP} = 2,\ \text{TWIS} = 2) = 0.1332$</td></tr>
<tr><td>Re = 2</td><td>TWIS = 2</td><td>NC = 2</td><td>HISL = 2</td><td>WTAB = 2</td><td>MG = 2</td></tr>
<tr><td colspan="6">$P(\text{Tr} = 1 \mid \text{Re} = 2,\ \text{TWIS} = 2,\ \text{NC} = 2,\ \text{HISL} = 2,\ \text{WTAB} = 2,\ \text{MG} = 2) = 0.0001906$</td></tr>
<tr><td colspan="6">$P(\text{Tr} = 2 \mid \text{Re} = 2,\ \text{TWIS} = 2,\ \text{NC} = 2,\ \text{HISL} = 2,\ \text{WTAB} = 2,\ \text{MG} = 2) = 0.1231$</td></tr>
</table>

Table 10. Evaluation of buyer agent.

<table>
<tr><td colspan="2">ICSL = 2</td><td colspan="3">Re = 2</td><td colspan="3">Hva = 2</td><td colspan="3">GMA = 2</td></tr>
<tr><td colspan="11">$P(\text{ReoS} = 1 \mid \text{ICSL} = 2,\ \text{Re} = 2,\ \text{Hva} = 2,\ \text{GMA} = 2) = 0.0055728$</td></tr>
<tr><td colspan="11">$P(\text{ReoS} = 2 \mid \text{ICSL} = 2,\ \text{Re} = 2,\ \text{Hva} = 2,\ \text{GMA} = 2) = 0.2159$</td></tr>
<tr><td>CT = 2</td><td>Tr = 2</td><td>TWIS = 2</td><td>ATI = 2</td><td>Sy = 2</td><td>MG = 2</td><td>SGM = 2</td><td>DiCm = 2</td><td>CQ = 2</td><td>Comp = 2</td><td>Cf = 2</td></tr>
<tr><td colspan="11">$P\left(\text{TroS} = 1 \,\middle|\, \begin{array}{c}\text{CT} = 2,\ \text{Tr} = 2,\ \text{TWIS} = 2,\ \text{ATI} = 2, \text{Sy} = 2,\ \text{MG} = 2,\\ \text{SGM} = 2,\ \text{DiCm} = 2,\ \text{CQ} = 2,\ \text{Comp} = 2,\ \text{Cf} = 2\end{array}\right) = 1.5185 \times 10^{-8}$</td></tr>
<tr><td colspan="11">$P\left(\text{TroS} = 2 \,\middle|\, \begin{array}{c}\text{CT} = 2,\ \text{Tr} = 2,\ \text{TWIS} = 2,\ \text{ATI} = 2,\ \text{Sy} = 2,\ \text{MG} = 2,\\ \text{SGM} = 2,\ \text{DiCm} = 2,\ \text{CQ} = 2,\ \text{Comp} = 2,\ \text{Cf} = 2\end{array}\right) = 0.00339$</td></tr>
</table>

Compared with the critique of Corporation A, Corporation B, indeed, has a far higher probability of having an excellent reputation and being trustworthy. Under such circumstances, the buyer agent will choose Corporation B rather than Corporation A to be the most appropriate supplier based on the above information. In addition, it can be expected that Corporation B will have an even higher probability to have an excellent evaluation if it also possesses the strong intention to adapt the buyer's policy.

5. CONCLUSIONS

This study introduces a BBN-based multiagent system to select suppliers in an e-marketplace. Each supplier is represented as an intelligent agent, which possesses limited information of others. While the buyer agents enter the e-marketplace, they initialize to talk and distribute their belief to all supplier agents, and then collect information. After required communication to establish mutual trust, the buyer can make a decision via the inference of BBN-based LJF.

The following benefits can be achieved by the proposed approach.

(1) Under Bayesian inference networks, the established system can inherit the ability of both forward and backward inference. Forward inference is used to select suppliers with the buyers' criteria of evaluation. On the other hand, backward inference is to change or reselect suppliers while suppliers' information has been modified. The pool of supplier agents can recognize their critiques from buyer agents and try to adapt their respective strategies via communication.

(2) With help of information gathered from buyer agents, the candidate suppliers can reason and modify current strategy to adapt buyers' expectation. In addition, the inferior suppliers can also be easily identified by the buyer.

(3) In a virtual e-marketplace, each supplier agent will possess its own strategy and probability table to issue different adaptive actions after communicating with the buyer agent. The major differences from the above will render the opportunity of evaluation for buyer agents.

(4) The agent can take sensitivity analysis about the variable node to determine whether it would impact the whole inference result. If it does not have any contribution, the linkage will be erased.

This proposed multiagent-based supplier selection approach is robust, even though only two levels are utilized in all decision factors to illustrate its feasibility. For future study, the fuzzy evaluation set can be adapted to extend the flexibility of this study.

REFERENCES

1. D.M. McCutcheon and F.I. Stuart, Issues in the choice of supplier alliance partners, *Journal of Operations Management* **18**, 279–301, (2000).
2. C. Ellis, Making strategic alliances succeed, *Harvard Business* **74** (4), 8–10, (1996).
3. P.K. Humphreys, V.HY. Lo and R.T. McIvor, A decision support framework for strategic purchasing, *Journal of Materials Processing Technology* **107**, 353–362, (2000).
4. D. Sinclair, L. Hunter and P. Beaumont, Models of customer-supplier relations, *Journal of General Management* **22** (2), 56–75, (1996).
5. L.R. Smeltzer, The meaning and origin of trust in buyer-supplier relationships, *International Journal of Purchasing and Materials Management* **33** (1), 40–48, (1997).
6. K. Singh, The impact of technological complexity and interfirm cooperation on business survival, *Academy of Management Journal* **40** (2), 339–367, (1998).
7. F.I. Stuart and D.M. McCutcheon, Sustaining strategic supplier alliances: Profiling the dynamic requirements for continued development, *International Journal of Production and Operations Management* **16** (10), 5–22, (1996).
8. D.T. Wilson, An integrated model of buyer-seller relationships, *Journal of the Academy of Marketing Science* **23** (4), 335–345, (1995).
9. A. De Toni and G. Nassimbeni, Buyer-supplier operational practices, sourcing policies and plant performances: Results of an empirical research, *International Journal of Production Research* **37** (3), 597–619, (1999).
10. K.H. Joo, T. Kinoshita and N. Shiratori, Design and implementation of an agent-based grocery shopping system, *IEICE Transaction on Information and System* **E83-D** (11), 1940–1951, (2000).

11. H.C.W. Lau, S.K. Tso and J.K.L. Ho, Development of an intelligent task management system in a manufacturing information network, *Expert Systems with Applications* **15**, 165–179, (1998).
12. J. Hendler, Making sense out of agents, *IEEE Intelligent Systems* **14** (**2**), 32–37, (1999).
13. T.J. Rogers, R. Ross and V.S. Subrahmanian, IMPACT: A system for building agent applications, *Journal of Intelligent Information System* **14** (2/3), 95–113, (2000).
14. H. Hajji and B.H. Far, Distributed software agents for network fault management, *IEICE Transaction on Information and System* **E83-D** (4), 735–746, (2000).
15. W. Lam and F. Bacchus, Learning Bayesian belief networks: An approach based on the MDL principle, *Computational Intelligence* **10** (3), 269–293, (1994).
16. J. Gemela, Financial analysis using Bayesian networks, *Applied Stochastic Models in Business and Industry* **17**, 57–67, (2001).
17. A.Y. Tawfik and E.M. Neufeld, Temporal reasoning and Bayesian networks, *Computational Intelligence* **16** (3), 349–377, (2000).
18. H. Pan and L. Liu, Fuzzy Bayesian networks—A general formalism for representation, inference and learning with hybrid Bayesian networks, *International Journal of Pattern Recognition and Artificial Intelligence* **14** (7), 941–962, (2000).
19. B. McCabe, S.M. AbouRizk and R. Goebel, Belief networks for construction performance diagnostics, *Journal of Computing in Civil Engineering* **12** (2), 93–100, (1998).
20. P. Kontkanen, P. Myllymaki, T. Silander, H. Tirri and P. Grunwald, On predictive distributions and Bayesian networks, *Statistics and Computing* **10**, 39–54, (2000).
21. M. Studeny and R.R. Bouckaert, On chain graph models for description of conditional independence structures, *The Annals of Statistics* **26** (4), 1434–1495, (1998).
22. F.V. Jensen, S.L. Lauritzen and K.G. Olesen, Bayesian updating in causal probabilistic networks by local computations, *Computational Statistics Quarterly* **4**, 269–282, (1990).
23. A. Becker and D. Geiger, A sufficiently fast algorithm for finding close to optimal clique trees, *Artificial Intelligence* **125**, 3–17, (2001).
24. A. Dumitrescu, B. Gätner, S. Pedroni and E. Welzl, Enumerating triangulation paths, *Computational Geometry* **20**, 3–12, (2001).
25. Y. Xiang, Cooperative triangulation in MSBNs without revealing subnet structures, *Networks* **37** (1), 53–65, (2001).
26. Y. Xiang, A probabilistic framework for cooperative multi-agent distributed interpretation and optimization of communication, *Artificial Intelligence* **87**, 295–342, (1996).

APPENDIX

Table A1. Supplier's probability tableau.

Conditional Probability for MG-Tr Arc			Conditional Probability for TroS-MG Arc			Conditional Probability for MG-GMA Arc		
Tr	MG	Pr(Tr | MG)	MG	TroS	Pr(MG | TroS)	GMA	MG	Pr(GMA | MG)
1	1	0.82	1	1	0.51	1	1	0.72
	2	0.39		2	0.46		2	0.47
2	1	0.18	2	1	0.49	2	1	0.28
	2	0.61		2	0.54		2	0.53

Conditional Probability for TroS-GMA Arc			Conditional Probability for TroS-WTAB Arc			Conditional Probability for TroS-HISL Arc		
GMA	TroS	Pr(GMA | TroS)	WTAB	TroS	Pr(MG | TroS)	HISL	TroS	Pr(HISL | TroS)
1	1	0.39	1	1	0.36	1	1	0.22
	2	0.43		2	0.72		2	0.55
2	1	0.61	2	1	0.64	2	1	0.78
	2	0.57		2	0.28		2	0.45

Conditional Probability for TroS-NC Arc			Conditional Probability for TroS-TWIS Arc			Conditional Probability for GMA-HISL Arc		
NC	TroS	Pr(NC | TroS)	TWIS	TroS	Pr(TWIS | TroS)	HISL	GMA	Pr(GMA | TroS)
1	1	0.12	1	1	0.18	1	1	0.92
	2	0.43		2	0.55		2	0.45
2	1	0.88	2	1	0.82	2	1	0.08
	2	0.57		2	0.45		2	0.55

Conditional Probability for GMA-WTAB Arc			Conditional Probability for WTAB-Tr Arc			Conditional Probability for Sy-WTAB Arc		
WTAB	GMA	Pr(WTAB | GMA)	Tr	WTAB	Pr(Tr | WTAB)	WTAB	Sy	Pr(WTAB | Sy)
1	1	0.88	1	1	0.82	1	1	0.92
	2	0.36		2	0.12		2	0.45
2	1	0.12	2	1	0.18	2	1	0.08
	2	0.64		2	0.88		2	0.55

Conditional Probability for Sy-NC Arc			Conditional Probability for Sy-TWIS Arc			Conditional Probability for NC-HISL Arc		
NC	Sy	Pr(NC | Sy)	TWIS	Sy	Pr(TWIS | Sy)	HISL	NC	Pr(HISL | NC)
1	1	0.39	1	1	0.12	1	1	0.92
	2	0.12		2	0.09		2	0.35
2	1	0.61	2	1	0.88	2	1	0.08
	2	0.88		2	0.91		2	0.65

Conditional Probability for NC-Tr Arc			Conditional Probability for HISL-Tr Arc			Conditional Probability for Comp-NC Arc		
Tr	NC	Pr(Tr | NC)	TR	HISL	Pr(Tr | HISL)	NC	Comp	Pr(NC | Comp)
1	1	0.96	1	1	0.83	1	1	0.62
	2	0.55		2	0.23		2	0.16
2	1	0.04	2	1	0.17	2	1	0.38
	2	0.45		2	0.77		2	0.84

Table A1. (cont.)

Conditional Probability for Comp-TWIS Arc

TWIS	Comp	Pr(TWIS | Comp)
1	1	0.87
	2	0.09
2	1	0.13
	2	0.91

Conditional Probability for TWIS-Tr Arc

TR	TWIS	Pr(Tr | TWIS)
1	1	0.77
	2	0.14
2	1	0.23
	2	0.86

Conditional Probability for TWIS-Re Arc

Re	TWIS	Pr(Re | TWIS)
1	1	0.56
	2	0.19
2	1	0.44
	2	0.81

Conditional Probability for PVAP-Re Arc

Re	PVAP	Pr(Re | PVAP)
1	1	0.83
	2	0.07
2	1	0.17
	2	0.93

Conditional Probability for CR-Re Arc

Re	CR	Pr(Re | CR)
1	1	0.79
	2	0.66
2	1	0.21
	2	0.34

Conditional Probability for QR-Re Arc

Re	QR	Pr(Re | QR)
1	1	0.89
	2	0.48
2	1	0.11
	2	0.52

Conditional Probability for QR-Tr Arc

Tr	QR	Pr(Tr | QR)
1	1	0.97
	2	0.22
2	1	0.03
	2	0.78

Conditional Probability for ReoS-QR Arc

QR	ReoS	Pr(QR | ReoS)
1	1	0.23
	2	0.47
2	1	0.77
	2	0.53

Conditional Probability for ReoS-CR Arc

CR	ReoS	Pr(CR | ReoS)
1	1	0.12
	2	0.23
2	1	0.88
	2	0.77

Conditional Probability for ReoS-PVAP Arc

PVAP	ReoS	Pr(PVAP | ReoS)
1	1	0.21
	2	0.35
2	1	0.79
	2	0.65

Conditional Probability for ReoS-TWIS Arc

TWIS	ReoS	Pr(TWIS | ReoS)
1	1	0.55
	2	0.35
2	1	0.45
	2	0.65

Conditional Probability for Re-Tr Arc

Tr	Re	Pr(Tr | Re)
1	1	0.81
	2	0.23
2	1	0.19
	2	0.77

Table A2. Buyer's probability tableau.

Conditional Probability for Re-GMA Arc			Conditional Probability for Re-Hva Arc			Conditional Probability for Re-ICSL Arc		
GMA	Re	Pr(GMA | Re)	Hva	Re	Pr(Hva | Re)	ICSL	Re	Pr(ICSL | Re)
1	1	0.72	1	1	0.87	1	1	0.78
	2	0.11		2	0.09		2	0.27
2	1	0.28	2	1	0.13	2	1	0.22
	2	0.89		2	0.91		2	0.73
Conditional Probability for Re-ReoS Arc			Conditional Probability for Re-TWIS Arc			Conditional Probability for Tr-ICSL Arc		
ReoS	Re	Pr(ReoS | Re)	TWIS	Re	Pr(TWIS | Re)	ICSL	Tr	Pr(ICSL | Tr)
1	1	0.83	1	1	0.86	1	1	0.87
	2	0.43		2	0.10		2	0.27
2	1	0.17	2	1	0.14	2	1	0.13
	2	0.57		2	0.90		2	0.73
Conditional Probability for Tr-Cf Arc			Conditional Probability for Tr-TWIS Arc			Conditional Probability for Tr-ATI Arc		
Cf	Tr	Pr(Cf | Tr)	TWIS	Tr	Pr(TWIS | Tr)	ATI	Tr	Pr(ATI | Tr)
1	1	0.14	1	1	0.84	1	1	0.79
	2	0.17		2	0.03		2	0.06
2	1	0.86	2	1	0.16	2	1	0.21
	2	0.83		2	0.97		2	0.94
Conditional Probability for Tr-MG Arc			Conditional Probability for Tr-TroS Arc			Conditional Probability for GMA-ReoS Arc		
MG	Tr	Pr(MG | Tr)	TroS	Tr	Pr(TroS | Tr)	ReoS	GMA	Pr(ReoS | GMA)
1	1	0.83	1	1	0.83	1	1	0.97
	2	0.12		2	0.16		2	0.18
2	1	0.17	2	1	0.17	2	1	0.03
	2	0.88		2	0.84		2	0.82
Conditional Probability for Hva-ReoS Arc			Conditional Probability for ICSL-ReoS Arc			Conditional Probability for ICSL-TroS Arc		
ReoS	Hva	Pr(ReoS | Hva)	ReoS	ICSL	Pr(ReoS | ICSL)	TroS	ICSL	Pr(TroS | ICSL)
1	1	0.79	1	1	0.99	1	1	0.94
	2	0.16		2	0.45		2	0.12
2	1	0.21	2	1	0.01	2	1	0.06
	2	0.84		2	0.55		2	0.88
Conditional Probability for ReoS-Cf Arc			Conditional Probability for ReoS-CQ Arc			Conditional Probability for CQ-TroS Arc		
Cf	ReoS	Pr(Cf | ReoS)	CQ	ReoS	Pr(CQ | ReoS)	TroS	CQ	Pr(TroS | CQ)
1	1	0.55	1	1	0.91	1	1	0.95
	2	0.51		2	0.16		2	0.25
2	1	0.45	2	1	0.09	2	1	0.05
	2	0.49		2	0.84		2	0.75

Table A2. (cont.)

Conditional Probability for DiCm-TroS Arc			Conditional Probability for SGM-TroS Arc			Conditional Probability for MG-TroS Arc		
TroS	DiCm	Pr(TroS | DiCm)	TroS	SGM	Pr(TroS | SGM)	TroS	MG	Pr(TroS | MG)
1	1	0.81	1	1	0.81	1	1	0.88
	2	0.64		2	0.43		2	0.07
2	1	0.19	2	1	0.19	2	1	0.12
	2	0.36		2	0.57		2	0.93
Conditional Probability for Sy-TroS Arc			Conditional Probability for ATI-TroS Arc			Conditional Probability for TWIS-TroS Arc		
TroS	Sy	Pr(TroS | Sy)	TroS	ATI	Pr(TroS | ATI)	TroS	TWIS	Pr(TroS | TWIS)
1	1	0.65	1	1	0.97	1	1	0.91
	2	0.50		2	0.01		2	0.11
2	1	0.45	2	1	0.03	2	1	0.09
	2	0.50		2	0.99		2	0.89
Conditional Probability for CT-TroS Arc			Conditional Probability for Cf-TroS Arc			Conditional Probability for Comp-TroS Arc		
TroS	CT	Pr(TroS | CT)	TroS	Cf	Pr(TroS | Cf)	TroS	Comp	Pr(TroS | Comp)
1	1	0.55	1	1	0.19	1	1	0.47
	2	0.39		2	0.88		2	0.09
2	1	0.45	2	1	0.81	2	1	0.53
	2	0.61		2	0.12		2	0.91
Conditional Probability for CQ-TroS Arc								
TroS	CQ	Pr(TroS | CQ)						
1	1	0.96						
	2	0.29						
2	1	0.04						
	2	0.71						